Non compliance in organic certification: determinants for Italy

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Abstract

Organic certification is based on controls on operators, and verify if they are compliant with respect to organic regulations. Control procedures are a transaction cost that affect organic farming relative competiveness. Here we propose an analysis aiming at increasing the efficiency in the individuation of key risk factors in the organic certification process. The study refers to Italian organic farmers and represents an attempt to implement a risk based inspection scheme based on a statistical approach.

Introduction

Certification is a distinctive feature of organic farming, and a concrete tool to assure that organic production rules are fulfilled. However, organic certification costs represent an important competitive disadvantage for organic farming. An improvement in the efficiency of control procedures of organic control bodies may help in reducing this transaction cost, providing a basis for a general increase in organic farms competitiveness. Here we present the results of a study for risk based inspections aiming at facilitating the individuation of the main risk factors of non compliances for organic operators. The study is part of the EU research project CERTCOST. The general aim is to individuate key factors that are more likely to be associated to non compliances, using both parametric and non parametric approaches. Only non compliances that generate sanctions are considered, and classified according to their severeness. A general description of the sanction distribution for 2008 is provided, and the main outcomes of the statistical analyses are discussed, also in terms of potential further research in this field.

Materials and methods

Data are taken from a dataset developed in the CERTCOST EU Project, and are based on data from certification bodies from different Euroepan countries. Italian data are provided by ICEA, the main Italian certification body, and for 2008 consists of 9.351 farmers, of which 1219 also have a processing activity. The dataset contains information on structural-managerial characteristics (e.g. farm size, crops types, livestock types, product type), control data (type and number of controls) and

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sanctions data (type and number of sanctions). Explanatory variables have been discretised or dicothomised. Since no information is available about the type and severity of non-compliances, we use sanctions data as a proxy. Following Accredia guidelines, for each operator we have deduced the type of non-compliance encountered from the resulting sanctions. Sanctions have been grouped and recoded into two general categories: moderate sanctions, referring to irregularities, i.e. less severe non-compliances, and severe sanctions, referring to infringements, i.e. most severe non-compliances. See Tab. 1 for a description of sanctions type distribution. On average, nearly 11% of the Italian farms were sanctioned in 2008. Almost 75 % of the sanction imposed was less severe (slight and moderate sanctions), while the rest (25%) were enclosed in the most severe group (severe and extreme).

Tab.1: Distribution of sanctions by type, IT 2008.

Nr. of sanctions imposed on a farm	Number of operators		
	Moderate sanctions	Severe sanctions	Total
0	8.779	9.153	8.605
1	430	147	545
2	118	46	167
3	13	4	14
>4	11	1	20
Total sanctions	**751**	**255**	**1.006**

Source: CERTCOST database - ITALY 2008

Here we present results arising from two approaches: a parametric approach based on binary choice models, and a probabilistic approach based on Bayesian Networks (BN). The binary choice model here used is a logit model, based on logistic distribution, and allows to explain the presence of sanctions detected as function of a set of explanatory variables (Greene 2008). The logistic distribution has been preferred to the standard normal distribution as it has shown a better management of the extremely sparse data on sanctions in the sample. The unrestricted model consists of a wide explanatory variable set, with 46 variables referring to crop and livestock types (e.g. cereals, poultry, etc) , structural variables (e.g. utilisable arable area (UAA), livestock units activity, etc) and specific risk factors (occurrence of sanctions in the previous year). A backward stepwise procedure has been followed, testing for statistical significance of the single coefficients (at least 5% significance required) and eliminating those that proved to be not relevant. Finally, we have performed a LR test to consider the validity of the restricted model. The BN approach (Horvitz et al., 1988) builds up a network of connections among variables, and the links among variables are measured in terms of conditional probabilities. More specifically BNs are used to determine the conditional probability of non-compliance given a set of “evidences”, i.e. the actual occurrence of the event that a certain variable assumes a given value. For instance, we can infer the probability of getting an infringement if a farmer cultivates a specific crop. The impact of evidences on the network has been designed using the PC algorithm, while conditional probabilities have been computed through the expecation maximiisation procedure of Hugin 7.0 software. For both models, variables have been discretised or dichotomised.

Results

Results from logit regression and BN are summarised in Tab 2 and show the variables that have been found as relevant impact on the risk of moderate and severe sanctions. For the logit model, only variables resulting from the restricted model resulting from the stepwise estimation are listed (the final restricted model has passed the LR constraint test). For the BN model only variables showing a sensible impact on the probabilities of sanctions are considered. + and – signs are respectively meaning a positive or negative impact of the variable on the probability of a farmer to get at least one sanction. Labels in bold indicate variables that are relevant for both models.

Tab. 2: Variables affecting sanctions risk: results from logit regression, ICEA data 2008. Variables are dichotomised, unless differently specified

	Moderate Sanctions		Severe Sanctions	
	logit	bbn	logit	bbn
Crop and livestock types				
Cereals		+		+
Citrus		-		-
Dried pulses		+		+
Fresh vegetables			+	
Fruit	-			
Grapes	+		+	
Grassland	+		+	
Green fodder	**+**	**+**		
Industrial crops	-		+	
Olives				-
Poultry	+		+	
Structural factors				
Conventional UAA	-		**+**	**+**
GMO-risk crops (maize, soya)	-	+		+
Livestock Units <10			+	
Crop structure complexity*	**+**	**+**	**+**	**+**
Nr of products (nr)		+		
Processor	+		-	
UAA (ha)		+		+
Sanctions				
Moderate Sanctions in 2007	**+**	**+**	+	
Severe sanctions in 2007			**+**	**+**

*a Shannon index has been used for the logit models as a proxy of crop structure complexity, while the number of crops has been used for BN models;

Discussion

Results from Tab 2 indicate that among crop and livestock type category, logit and BN individuate different group of variables as relevant, with the only exception of "Green fodder", which is considered as a risk factor for moderate sanctions in both models. Also, while many risk factors are common for both moderate and severe sanctions, some variables are only relevant for one sanction type: "Fresh vegetables", "Fruit", "Olives". For what concerns the structural risk factors, "Conventional UAA" and "Crop structure complexity" are significant in both models, with the second one found as relevant for both the moderate and severe sanction risk. Controversial results are found for "GMO-risk crops" in the moderate sanction models. Finally, almost univocal results are found for moderate and severe sanctions issued in 2007: it is interesting to note how the risk of moderate sanctions is not affected by the occurrence of severe sanctions in 2007, while some evidence from the logit model indicate that 2007 moderate sanctions increase the risk of severe sanctions. The occurrence of sanctions in 2007 can be interpreted as a proxy of the farmers' individual effect, like farmers' attitude to fraud, managerial errors, geographical aspects, etc. Unfortunately the scientific literature on these aspects is extremely scarce. Gambelli and Solfanelli (2009) have performed similar analysis for moderate sanctions using a dataset of Italian farm from another certification body, testing different farm types risk of non-compliances. Similar results are found in particular for what concerns the key role of the sanctions issued in the previous years. Also, the negative effect on sanctions risk of citrus and olives and the positive one of livestock related crops (grassland, green fodder, mais) are confirmed in both studies.

Conclusions

The approach we have used for this study show encouraging results and can be considered as complimentary tools for understanding risk patterns in the organic certification schemes. It is necessary to consider that results cannot be generalised and should be considered relevant only for the specific control body that provided the dataset. Further work is needed, in particular for what concerns the analysis of different combination of variables and the elaboration of more powerful econometric models. For what concerns the first aspect, it is reasonable to suppose that some variables could be considered at risk only when combined with other. For what concerns the second aspect, the incorporation of the time dimension and the use of count data models, which also explain the actual number of sanction detected, could be considered as interesting options to consider. However, the general approach focussing on a standardisation of sanction types and the use of probabilistic models can be considered a promising step towards the definition of a risk based inspection systems that could improve efficiency in the organic sector.

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